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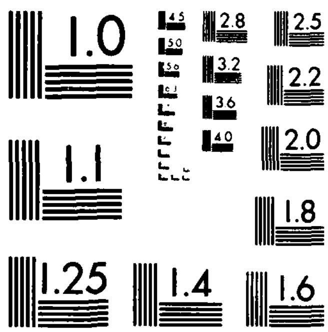

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RSRE MEMORANDUM No. 3743

ROYAL SIGNALS & RADAR ESTABLISHMENT

EDGE DETECTION IN SAR IMAGERY USING GRADIENT OPERATORS

Author : Dr S C Giess

PROCUREMENT EXECUTIVE,
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ROYAL SIGNALS AND RADAR ESTABLISHMENT

Memorandum 3743

Title: Edge detection in SAR imagery using gradient operators

Author: Dr S C Giess

Date:

SUMMARY

This memo presents a study of the problems involved in the detection of edge features on high resolution Synthetic Aperture Radar (SAR) images using gradient operators. An algorithm, proposed recently as a model of the human visual system, which embodied these techniques was investigated and found to give poor performance on SAR images. The reasons for this poor performance were studied and the conclusion drawn that edge detection by gradient operators alone was not appropriate for SAR images.

INTRODUCTION

The ultimate goal of this work is the full automatic analysis of SAR images. The fist essential step in this process is to be able to split the image into its component parts.

The problem of devising automatic methods of area and boundary segmentation has been a major area of work in the field of pattern recognition over the last twenty years (1), (2). For all the effort only partial success has been achieved and this for circumstances that are well controlled. Many different avenues have been explored: some from the point of view of attempting to understand the mechanisms at work in animal and human vision and then apply these algorithms to the computer environment; others have adopted the approach of finding a technique that works just for the particular problem in hand.

I shall show that the segmentation of SAR imagery presents a greater challenge than the segmentation of ordinary optical or infra-red images and furthermore it poses a severe test for any model of the human vision system. I have focussed the study onto one particular model of human visual edge detection, that put forward by Marr & Hildreth (3) in 1981. This model was chosen for three reasons:

a. By inspection we can segment SAR images easily and so the model, if correct, should be applicable to our particular problem.

b. It uses an edge detection technique that is superficially more capable of handling SAR speckle (see later) than many others in the literature. See the review by Chin & Yeh (4), Lee (5) and Suk & Hong (6).

c. It has a methodology that lends itself to adaptive programming. This would enable information on faint but extended features to be extracted only if thought necessary.

SAR IMAGERY

The production of high resolution SAR images has been described elsewhere (7). For the purposes of this study a SAR image is a 2 dimensional array of real numbers, each number representing the magnitude of the scattered electric field averaged over the sampling area. Fig 1 is a typical image being 512 x 512 pixels and having a linear grey scale, peak white being the highest amplitude. Inspection of Fig 1 shows the most notable difference of SAR imagery compared to ordinary optical photographs, namely the speckle structure of all parts of the image. This speckle arises from the coherent nature of the radar system and is the same as the speckle seen when a rough surface is illuminated with laser light. In both cases it is caused by the interference, at the detector, of the scattered radiation which has travelled along differing path lengths due to the rough surface.

Speckle on SAR images has a K-distributed structure. This K-distribution has been shown to arise from an underlying, gamma distributed, radar cross-section combined with a superimposed Gaussian speckle (8)&(9). Concentrating on the speckle then the amplitude of the scattered field is represented by a Rayleigh distribution whose local mean is determined by the underlying gamma function. The Rayleigh has the form

$$p(r) = \frac{r}{\sigma^2} \exp\left(\frac{-r^2}{2\sigma^2}\right)$$

where p(r)dr is the probability that the resultant amplitude lies in the range r to r+dr for a distribution of width σ.

This speckle phenomenon adds a further twist to the problem of image analysis by virtue of its multiplicative nature. Most work on image analysis has assumed that any "noise" component is due to system imperfections, further it is both additive to what is essentially a "smooth" structure and has gaussian statistics. However on a SAR image the speckle "noise" IS the image and not merely a system imperfection. Figs 2a-c illustrates this difference. Fig 2a shows a cut through a reflecting/scattering surface taken across the boundary of two regions of differing mean reflectivity.

Fig 2b shows the boundary as it may be observed with an incoherent imaging system which adds gaussian noise to the final image. It is obvious that an appropriately chosen amplitude threshold will segment the image into the two regions.

Fig 2c shows the same boundary as seen through a coherent system. Here the intrinsic "noisiness" of the image means that the image cannot be satisfactorily separated into the two regions by means of a simple threshold. However it is possible, by eye, to decide that there is a boundary present. This decision relies on the eye being able to average over a region of the image in such a way that the underlying change of reflectivity is detected.

A detailed examination of fig 1 for boundaries shows that they can be detected by eye even when they are markedly discontinuous provided a large enough fraction of the image is visible at the same time. This ability to discern "long range" separated structure with ease is in marked contrast to most edge detection algorithms which are local in operation. This suggests that the eye does some form of adaptive area processing. Marr and Hildreths theory addresses aspects of this point. It may also suggest the use of a priori knowledge of the form that structures seen on a map may be expected to take. If this is so then satisfactory segmentation of images may not be possible using simple stand alone algorithms.

MARR AND HILDRETHS THEORY

Marr and Hildreth (3) proposed a theory of edge detection which they considered fitted some physiological findings. Edges are detected in the model by their spatial coincidence on versions of the original scene that have been smoothed by differing degrees. Their reasoning is as follows:

Let us consider band-pass filtering an image with non-overlapping filters. Now the noise present on the original image will have a spatial spectrum whose components are independent. Therefore the positions of the noise structures on the band limited images will be uncorrelated. However, a structure like a boundary will have a spectrum whose components are related, so the band limited images will exhibit spatial correlation.

The spectral extent of the boundary will of course depend upon the sharpness of the transition implying that many filters may be needed to encompass all possibilities.

Marr and Hildreth considered that the 2-Dimensional Gaussian

$$G(r) = \frac{1}{2\pi\sigma^2} \exp\left(\frac{-r^2}{2\sigma^2}\right)$$

where r=the radial distance from the origin and σ the width, was the optimum choice of filter function. Further they considered that image segmentation was possible using just 2 filter widths. The filtered image is produced by convolving the original image I with the Gaussian (G*I). The edges on these convolved images are found by applying the orientation independent Laplacian operator $\nabla^2 = \frac{1}{r}\frac{\partial}{\partial r}\left(r\frac{\partial}{\partial r}\right)$ to the convolved images and locating the points where

$$\nabla^2 (G*I) = 0.$$

Then the positions of these zero points on the different images are compared. Finally the points where they coincide are labelled as being part of an edge.

Marr and Hildreth pointed out that the Laplacian could be taken inside the convolution and so the original image could be convolved with $\nabla^2 G$ directly

$$\nabla^2 G = \frac{-1}{\pi\sigma^4} \left\{1 - \frac{r^2}{\sigma^2}\right\} \exp\left(\frac{-r^2}{2\sigma^2}\right)$$

thereby saving a step.

This theory has several attractive features. Firstly it can be considered in a quantitive manner unlike some other operators which are chosen on an ad hoc basis. Secondly the processing has possibilities for parallel architecture. Thirdly the widths of the Gaussians can be altered so as to be able to cope with differing signal to noise levels (for the incoherent case) in a way that is consistent with our ability to locate edges of faint boundaries under noisy conditions.

ALGORITHM ASSESSMENT

It was decided to apply the edge detecting algorithm to a synthetic image. The image chosen, Fig 3a, was 128 x 128 pixels in extent and consisted of a square of uniform underlying brightness (sigma = 20) and size 47 x 47 surrounded by a background of lower underlying brightness (sigma = 10). Each pixel value was independent and drawn from a Rayleigh distributed random number generator with the appropriate value of sigma. No attempt was made to introduce the effects of real radar systems in terms of range and cross-range correlations.

Figs 3b and 3c show the result of convolving Fig 3a with Gaussians of sigma width 2 and 4 units of pixel spacing respectively. The grey boundaries are those areas for which there is no valid convolution value available.

Figs 3d and 3e show the result of applying the Laplacian operator to figs 3b and 3c respectively. Finally figs 3f-3i shows the zero crossing spatial coincidence results. Here a point is plotted white if the values at that same point on figs 3d and 3e are both simultaneously within a threshold set about zero. The thresholds chosen for figs 3f-3i are 1.0, 0.2, 0.1 and 0.05 respectively.

A study of figs 3d and 3e shows the boundary of the square quite clearly. However while the same boundary can be seen on figs 3g and 3h it is apparent that the residual noise dominates the image. Decreasing the zero crossing threshold reduces both the wanted crossing points as well as the unwanted noise points. It is worth considering this coincidence operation in more detail. Fig 4 shows the result of convolving a single dimensional top hat function with Gaussians of different widths and then taking the second derivative. It is apparent that the positions of the zero crossing points for the first Gaussian are displaced relative to those for the second. Hence a simple coincidence detector will not necessarily work. Moreover the magnitude of this shift is dependent on the structure of the original image and so it is not even possible to use offset coincidence. The simple expedient of allowing a zero crossing threshold is one way around the problem, but as can be seen on figs 3f-3i, it has the effect of allowing random zero crossings to be treated as valid edges.

A better solution would be to use a convolving function that gives resolution independent second differential zero crossing points. One function that has this property is the top hat or cyclinder function as is demonstrated in fig 5.

The results of applying this cylindrical function with radii of 4 and 8 pixel spacing units to the original image, fig 6a, are given in figs 6b to 6i. Figs 6b and 6c are the convolution results, figs 6d and 6e are the results of the Laplacian operator on figs 6b and 6c. In these cases the Laplacian had to be applied explicity since (∇^2 top hat) has infinities. The form of the operator was

$$\nabla^2 = U_{x-1,y} - 2U_{x,y} + U_{x+1,y} \quad + \quad U_{x,y-1} - 2U_{x,y} + U_{x,y-1}$$

where $U_{x,y}$ is the value of the image at coordinates x,y. (It should be noted that this operator will have errors for functions which change rapidly on scale sizes of the order of the pixel spacing).

As can be seen from figs 6f to 6i, which are the coincidence results with thresholds of 1.0, 0.2, 0.1 and 0.05 respectively, there is little evidence of the detection of the edge.

ASSESSMENT CONCLUSIONS

The principal conclusion that can be drawn from the cylinder result is that the Gaussian only gave satisfactory results because it suppressed the small scale structure. We know that the Fourier transform of a Gaussian is simply another Gaussian, also the Fourier transform of a cylinder is an Airy function. Therefore the convolution of the image with a Gaussian would result in the suppression of the higher spatial frequency structure. However the convolution with the cylinder still leaves residual small scale structure. This is important as the Laplacian operator is very sensitive to small scale structures because of the large rates of change of gradient implicit in their existence.

Clearly we are interested in a detection system that is sensitive to large scale changes due to boundaries and not small scale changes due to a residual noise component. As such the Laplacian would seem to be a poor choice of operator; presumably this is why the original algorithm relies heavily on the

spectral properties of the Gaussian. Fig 7a shows a cut through the image convolved with the Gaussian (fig 3c). The boundary of the square can be clearly seen. Fig 7b shows the corresponding cut through the Laplacian operated image (fig 3e). Here the existence of the edge is by no means as clear.

Fig 8a is a cut through the image convolved with the cylinder (fig 6c). Note that the boundary can still be easily seen, note also the small scale noise structure present. Fig 8b is the corresponding cut through the Laplacian processed image (fig 6e). Here I suggest it is not possible to deduce the existence of the edge from the data as the second derivative values due to the small scale structure are dominant.

OVERALL CONCLUSIONS

It is apparent from this study that the methodology proposed by Marr and Hildreth for detecting edges will not be outstandingly good at segmenting SAR images. This point coupled with our own ability to see these regions on SAR images casts doubt on the validity of the claim that the human visual process can be modelled in the manner they proposed. More recent work by Morgan et al (10) showed that Marr and Hildreths algorithm needed a non-linear prefilter in order to account for other known physiological effects. However it is not obvious that such a filter would dramatically improve the performance in our situation. An analysis of the underlying statistics of objects on SAR images (11) indicates that all simple edge detecting algorithms of the type analysed here will give poor results for coherent imagery. Structural prior knowledge has to be included for segmentation to be successful.

Finally, the work reported here demonstrates yet again both the great sophistication of the human visual system and also its non-amenability to analysis into constituent parts by means of simple experiments.

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FIGURE 1

FIG. 2a

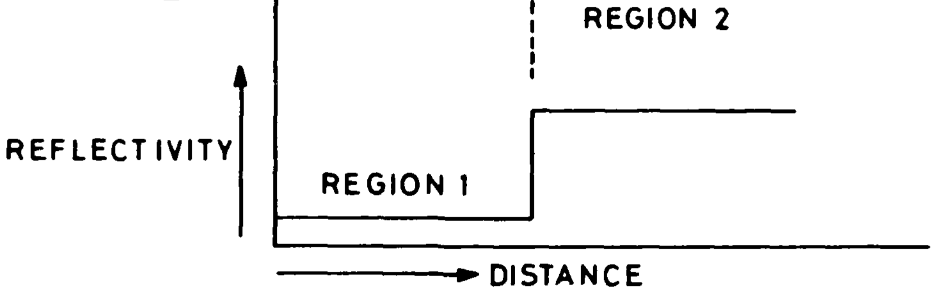


FIG. 2b

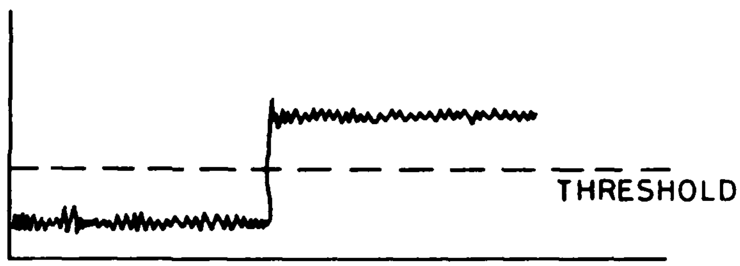
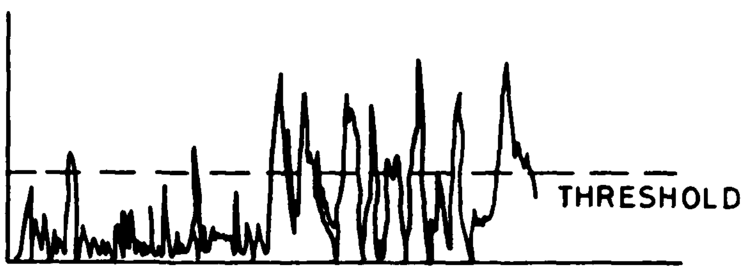


FIG. 2c



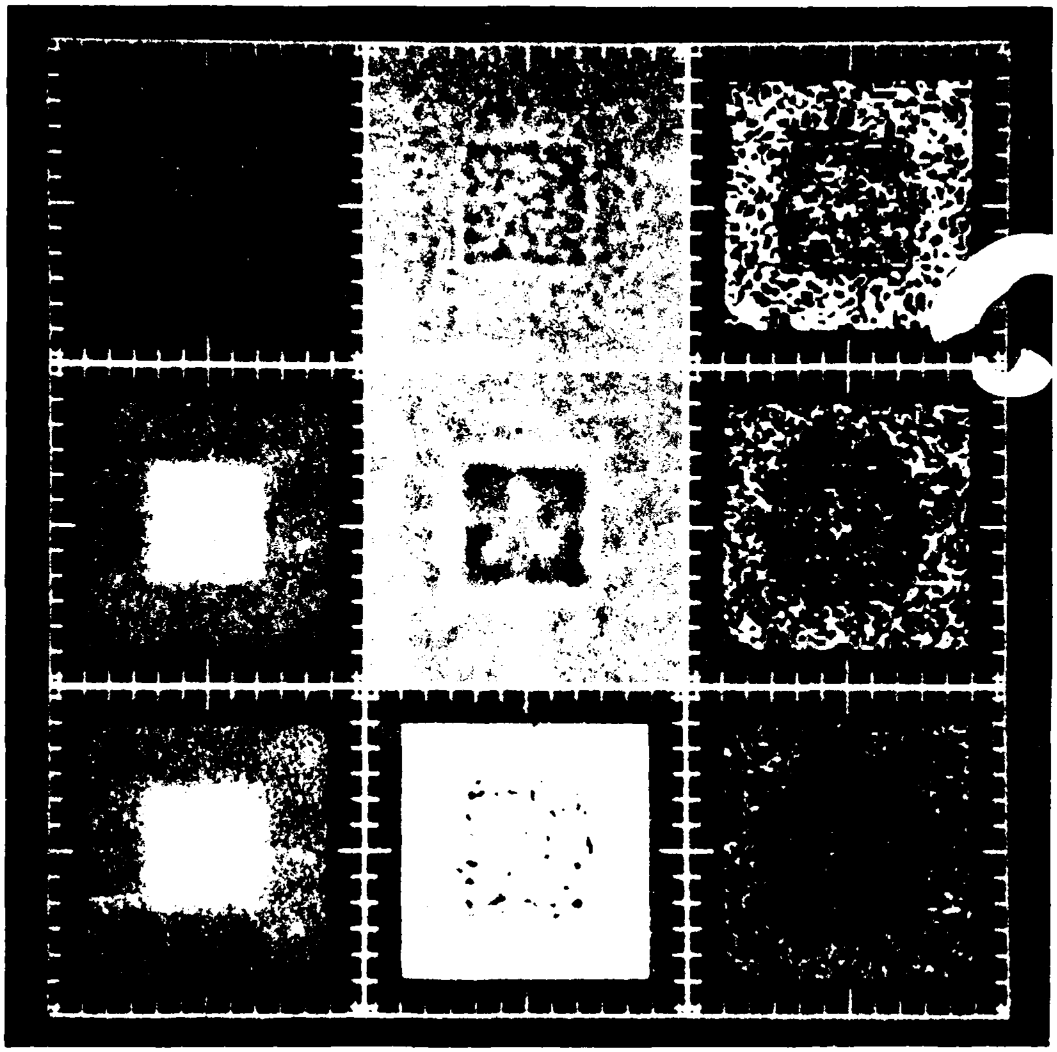


FIGURE 3

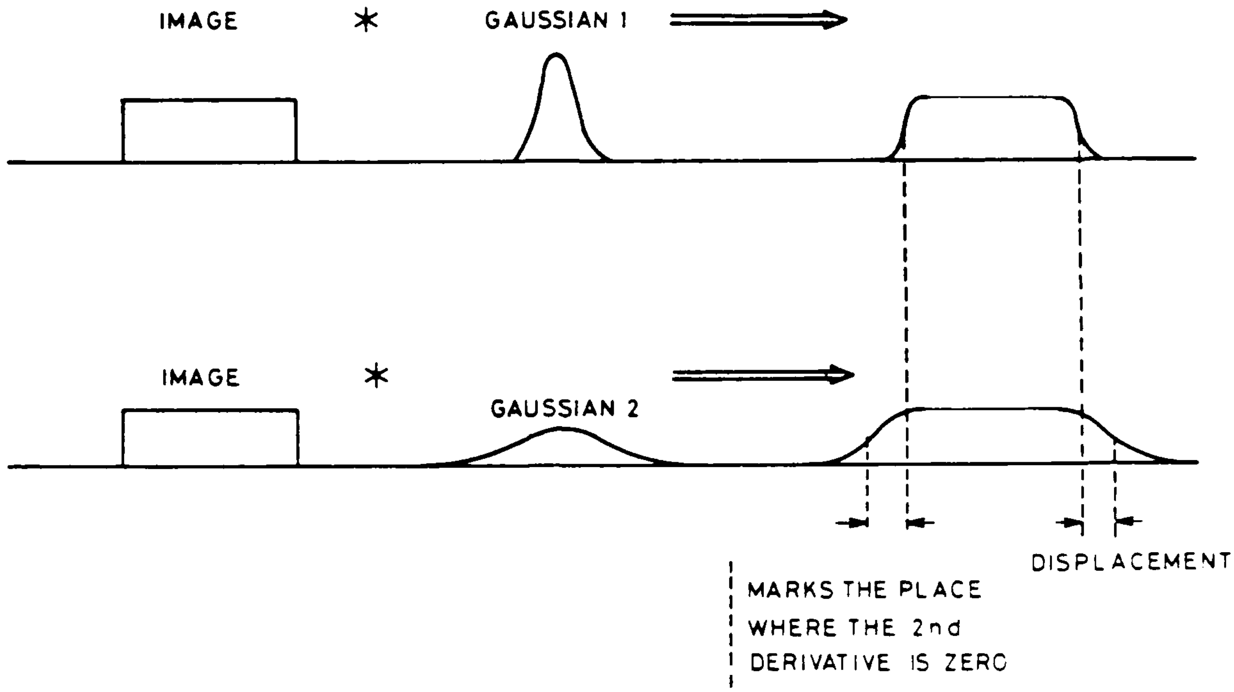


IMAGE
*
GAUSSIAN 1
IMAGE
*
GAUSSIAN 2
DISPLACEMENT
MARKS THE PLACE
WHERE THE 2nd
DERIVATIVE IS ZERO

FIG 4

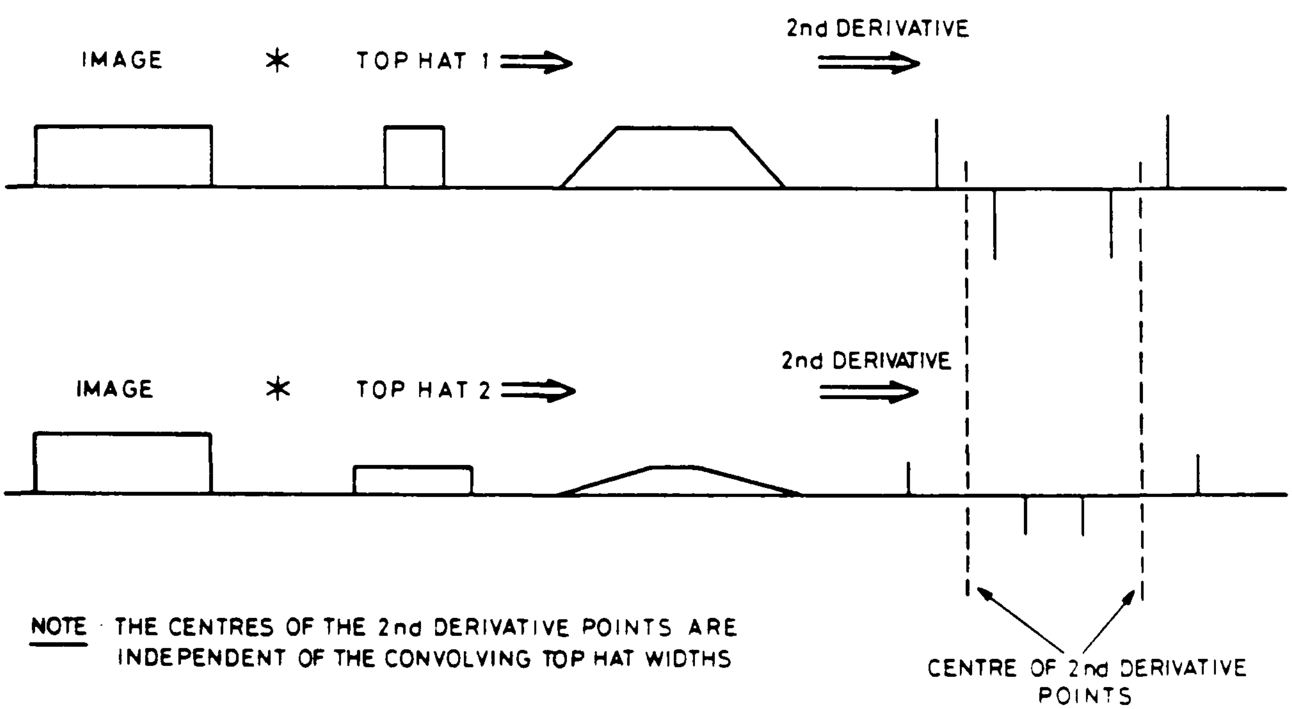


IMAGE
*
TOP HAT 1
2nd DERIVATIVE
IMAGE
*
TOP HAT 2
2nd DERIVATIVE
NOTE · THE CENTRES OF THE 2nd DERIVATIVE POINTS ARE
INDEPENDENT OF THE CONVOLVING TOP HAT WIDTHS
CENTRE OF 2nd DERIVATIVE
POINTS

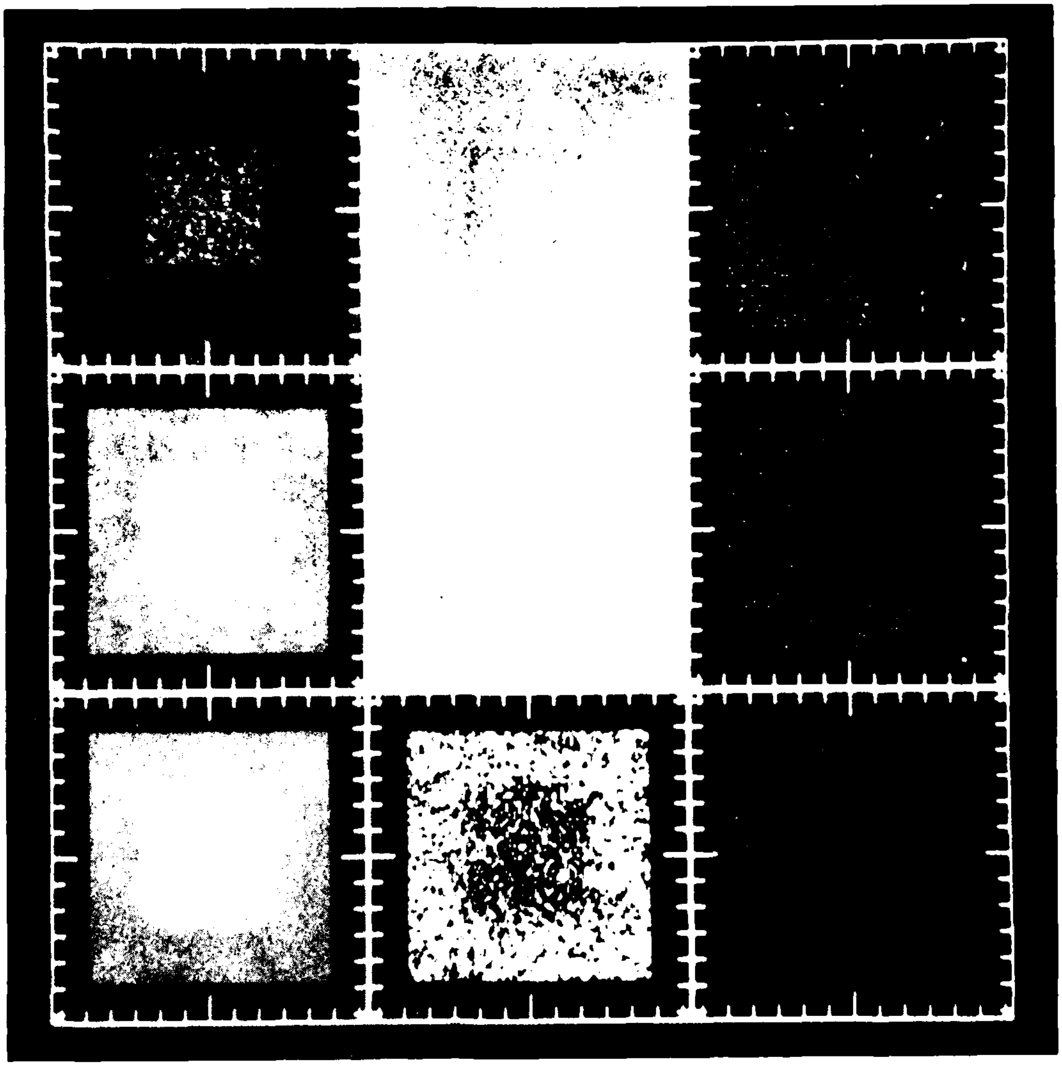
FIG 5

(d)

(a) (g)

(b) (h)

(c) (i)



(f)

FIGURE 6

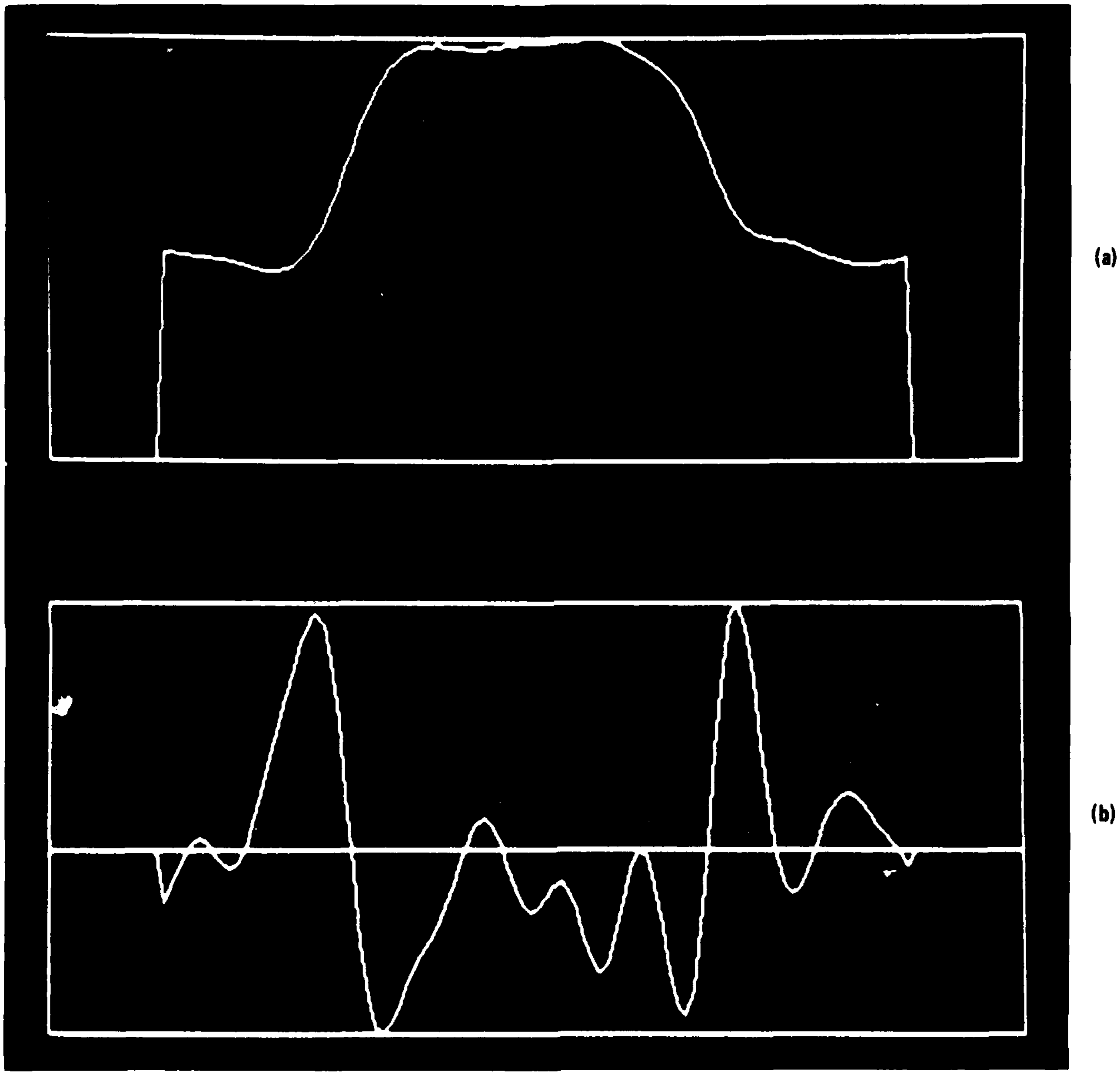
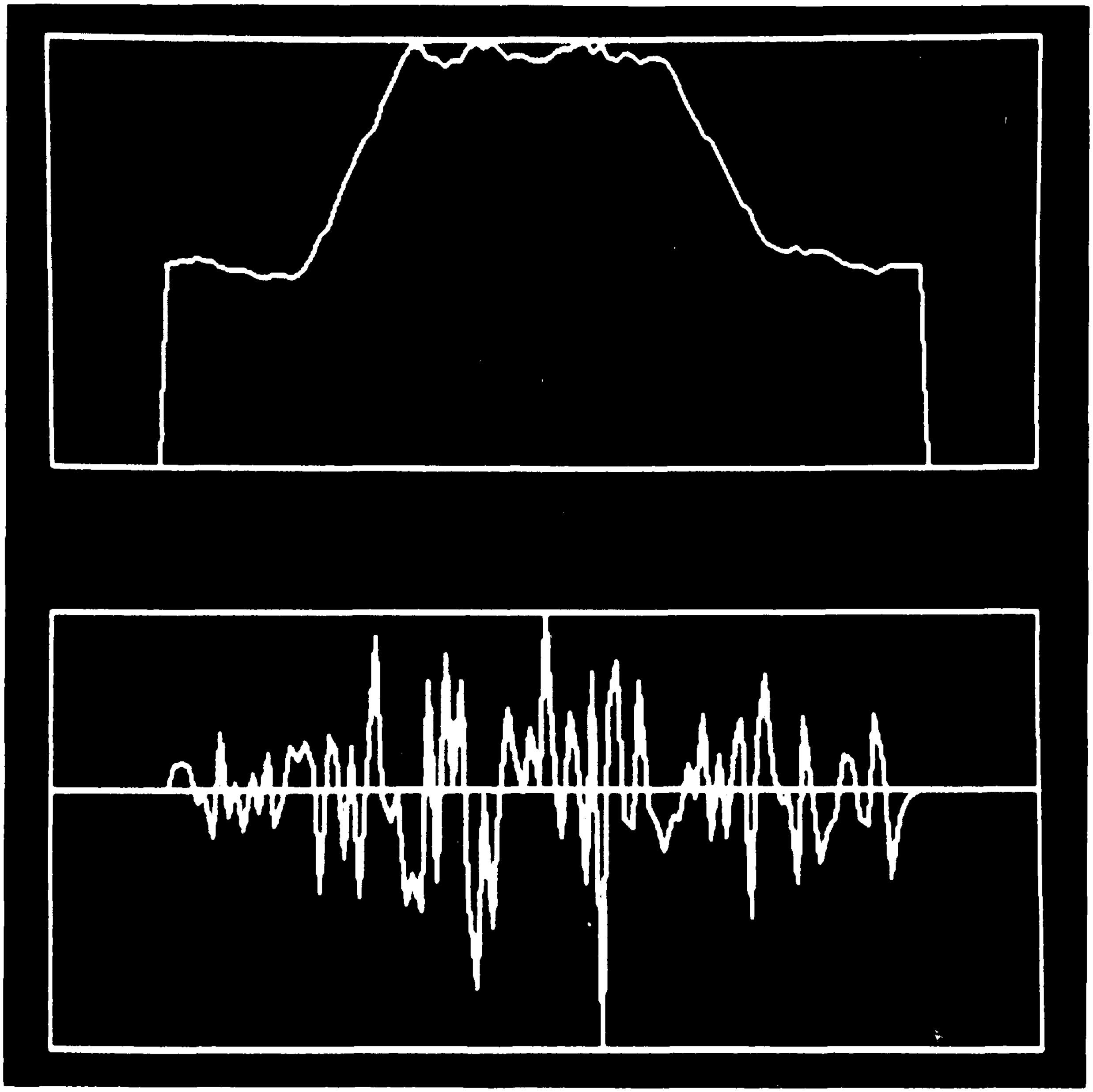


FIGURE 7



(a)

(b)

FIGURE 8

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7a. Title in Foreign Language (in the case of translations)

7b. Presented at (for conference papers) Title, place and date of conference

8. Author 1 Surname, initials	9(a) Author 2	9(b) Authors 3,4...	10. Date	pp. ref.
Giess, S C				

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Abstract

This memo presents a study of the problems involved in the detection of edge features on high resolution Synthetic Aperture Radar (SAR) images using gradient operators. An algorithm, proposed recently as a model of the human visual system, which embodied these techniques was investigated and found to give poor performance on SAR images. The reasons for this poor performance were studied and the conclusion drawn that edge detection by gradient operators alone was not appropriate for SAR images.

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